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PARAMETER IDENTIFICATION AND SENSITIVITY ANALYSIS FOR A ROBOTIC MANIPULATOR ARM

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Abstract

This paper describes the development of a nonlinear dynamic model for large oscillations of a robotic manipulator arm about a single joint. Optimization routines are formulated and implemented for the identification of electrical and physical parameters from dynamic data taken from an industrial robot arm. Special attention is given to difficulties caused by large sensitivity of the model with respect to unknown parameters. Performance of the parameter identification algorithm is improved by choosing a control input that allows actuator emf to be included in an electro-mechanical model of the manipulator system.

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1. INTRODUCTION

The purpose of this research is to develop and investigate methods for identifying parameters in a dynamic model of a robotic manipulator. Such methods are important for determining models that serve as the basis for the design of manipulators and of control algorithms for manipulators [2, 7, 8]. Because the parameter identification must be based on input and output data from an assembled manipulator, which acts under gravity and has possibly complicated joint friction, the dynamic model is a nonlinear differential equation, which must be solved numerically.

The approach used to date is to employ a nonlinear search routine to minimize a quadratic fit-to-data criterion formed using the experimental data and the solution to the model equation. This method has been applied to a Unimation 600 Puma arm, with data obtained by F. W. Harrison in the Intelligent Systems Robotics Laboratory at the NASA Langley Research Center.

Section 2 describes the mathematical model of the manipulator arm and the parameters to be identified. Section 3 describes the parameter identification scheme and the computer algorithms used. In Section 4, the experiment is discussed in more detail, along with some preliminary data reduction and analysis of motor parameters.

In Section 5, we analyze the sensitivity of the manipulator model with respect to small perturbations in parameters. The solution to the model equation is very sensitive to such perturbations when the input to the model is the torque applied to the arm. In some parameter estimation problems, high parameter sensitivity is desirable because it allows unknown parameters to be estimated from noisy data. However, the experimental data that we have used in this research has very little noise, and very high parameter sensitivity repeatedly has prevented the search routine in our identification procedure from converging.

Also, we should note that a model very sensitive to parameter variations produces unreliable simulations, since the model parameters are impossible to identify exactly and since some physical parameters in any manipulator can vary with time. The analysis in Section 5 suggests both the cause and the cure for the undesirably large parameter sensitivity. We reduce this sensitivity by including the back electromotive force in the equation of motion for the model and making the input the motor voltage rather than the torque exerted on the arm.

In Section 6, we discuss the results of the parameter estimation routines and derive values for electrical and mechanical model parameters that are constant over the duration of our experiment.

2. MANIPULATOR MODEL

In the example in this paper, we attempt to identify inertia parameters and joint damping for the robot shown in Figure 1. To minimize the number of unknown parameters, we chose input/output data from an experiment with all joints but the shoulder locked. The manipulator arm then is a rigid body moving in a vertical plane, with the one degree of freedom. The equation of motion for the model is

$$I_0\ddot{\theta} - mgr\sin\theta + h(\dot{\theta}) = Nu(t) \qquad (2.1)$$

where $\theta = \theta_2$ (see Figure 1) is the angle between the arm and the upward vertical and u is the control torque supplied by the electric motor (actuator) at the joint in question. The damping term $h(\dot{\theta})$ represents friction in both the joint and the motor; I_0 is the moment of inertia about the appropriate joint, m is the mass of the arm, g is the acceleration of gravity, and r is the distance from the joint axis to the arm's center of mass, and N is the gear ratio.

We will also use the following equations relating motor torque, motor current (i), and motor terminal voltage (v)

$$u = K_t i \tag{2.2}$$

$$Ri + K_e N\dot{\theta} = v \tag{2.3}$$

where K_t is the torque constant, R is the motor resistance, and K_e is the back emf constant. Equation (2.3) assumes the motor inductance is negligible. The accuracy of these equations is discussed in Section 4.

The basic idea of the parameter identification scheme is to find parameters for (2.1) so that the solution to this differential equation matches the measured angle as closely as possible at the sampling times. Because we cannot identify all of the parameters in (2.1) from the experiment described, we must define a minimal set of parameters for this model. Therefore, we rewrite (2.1) as

$$\ddot{\theta} - \alpha \sin \theta + f(c_1, c_2, \dot{\theta}) = \beta u(t) \tag{2.4}$$

where $\alpha = mgr/I_0$, $\beta = 1/I_0$, and we have parameterized the damping term $h(\dot{\theta})$ in (2.1) as $f(c_1, c_2, \dot{\theta})$.

In this paper we will use a piecewise linear, direction-dependent damping model of the form

$$f(\dot{\theta}) = \begin{cases} c_1\dot{\theta} & \dot{\theta} > 0, \\ c_2\dot{\theta}, & \dot{\theta} < 0. \end{cases} \tag{2.5}$$

Note that this model allows linear viscous damping as the special case $c_1 = c_2$, but allows the parameter estimator to check for asymmetry in the damping parameters. Our best results have been obtained with this friction model. A comparison of (2.5) with linear and quadratic damping may be found in [3].

We will refer to the set of parameters in (2.2) by the parameter vector

$$q = [\ \alpha\ \beta\ c_1\ c_2\ \ldots]. \tag{2.6}$$

3. PARAMETER IDENTIFICATION

An experiment performed on a time interval $[t_0, t_f]$ yields data $u(t_i)$ and $y(t_i)$, $t_i = t_0, t_0 + t_s, \ldots, t_f$, where $y(t_i)$ is the joint angle measured from the vertical at time t_i. We denote the measured angle (i.e., the data) by $y(t_i)$ to distinguish it from $\theta(t)$, the solution to the model equation (2.1). For the data used here, the sampling rate was 30 Hertz, so that

$$t_s = t_{i+1} - t_i = 1/30 \text{ sec.} \tag{3.1}$$

With the known command torque $u(t)$ and a set of trial parameters, we solve (2.4) on the interval $[t_0, t_f]$ and form the fit-to-data criterion

$$J(q) = \sum [\,\theta(t_i) - y(t_i)]^2. \tag{3.2}$$

The parameter identification then consists of finding the parameter vector $\mathbf{q}$ to minimize $J(\mathbf{q})$. Usually, we take the initial time $t_0 > 1$ sec. because we suspect some error in the data near the beginning of the experiment due to transients in electronics. Therefore, in some cases we know that the initial angular velocity is zero, but in most cases we must estimate it using finite differences obtained from the position measurement.

To solve (2.4), we use a fourth-order Runge-Kutta algorithm with variable step size [5]. We tried using the numerical integrators DGEAR and DVERK in the IMSL library, but both of these routines often hung up--i.e., the step size was reduced to zero--where the manipulator arm turned. This was especially troublesome for models with piecewise continuous damping and Coulomb friction. The step-size control in our final Runge-Kutta routine does not allow the step size to fall below a specified minimum.

For minimizing $J(q)$ we used the subroutine ZXSSQ from the IMSL library, which is a Levenberg-Marquardt algorithm [4] that approximates gradients by finite differences. It also estimates the Hessian. Hence we assume certain smoothness and local convexity of $J(\mathbf{q})$ and the performance of the algorithm indicates that these assumptions are valid.

4. DATA COLLECTION AND ANALYSIS

Experimental data was collected by F. W. Harrison in the Intelligent Systems Robotics Laboratory (ISRL) at NASA Langley Research Center. The subject of the experiments was a UNIMATE PUMA industrial robot with six degrees of freedom. A schematic [1] of the robot arm with rotational joints is shown in Figure 1. The experiment described below was performed by rotating only the shoulder (joint 2) with joint 1 fixed and all other joints locked in a collinear position.

The purpose of this experiment was to gather input and output data for dynamic models. The arm was initialized in a vertical, upright position and then commanded to rotate about joint 2 with varying frequency and amplitude. During this oscillation, 512 measurements of the joint angle in radians (Figure 2), the motor current (Figure 3), and the motor terminal voltage (Figure 4) were taken at a frequency of 30 Hertz. The motor current was measured by the voltage drop across a known resistance. The angular velocity of the arm calculated by central differences is shown in Figure 5.

A linear least-squares regression was performed to identify motor parameters and test the validity of motor equation (2.3) which assumes negligible inductance. Regression identified the motor resistance as 2.59 ohms and the back emf constant as 0.238 volts-sec after factoring out a gear ratio for joint 2 of 107.8. The gear ratio was supplied by Don Soloway of ISRL. The left and right-hand sides of equation (2.3) for these parameter values are compared in Figure 6 where they show close agreement.

A static experiment had been earlier performed on joint 2 to test the validity of equation (2.2) which assumes a linear relationship between motor torque and motor current. The correlation coefficient was calculated as

0.999. This experiment and data are discussed in [3]. For this reason the current data taken in this experiment was used as an accurate measurement of motor torque after multiplying by the torque constant. Since in the units used here the torque constant and back emf constant are numerically equal, we used $K_t = .238$ N-m/amp in equation (2.2).

5. SENSITIVITY ANALYSIS

We have found that the solution to (2.4) is very sensitive with respect to small variations in the coefficients or the initial conditions when the input u is the torque exerted by the motor. Figures 7 and 8 show the effect on a solution to (2.4) of one percent pertubations in the parameters β and c_1.

Tables 1A and 1B illustrate the effect of this high parameter sensitivity on the parameter identification algorithm. The sensitivity has prevented us from obtaining any reasonable fit to the data over the entire experiment. The parameters for iteration 3 in Table 1A yield the best fit that we have found for the data between 1 second and 6 seconds. The large variations in the model trajectory produced by small parameter variations lead to large and unpredictable variations in the objective J. For this reason the numerical optimization scheme can not be relied upon to locate good model parameters even when they exist and lie close to the initial guess (compare Tables 1A and 1B).

To analyze the sensitivity of the model in Section 2, we let $z(t)$ be the partial derivative of $\theta(t)$ with respect to one of the parameters α, β, c_1, c_2. Then $z(t)$ satisfies

$$\ddot{z}(t) - a_1(t)z(t) + a_2(t)\dot{z}(t) = g(t) \tag{5.1}$$

where

$$a_1(t) = \alpha \cos\theta(t), \tag{5.2}$$

and

$$a_2(t) = \begin{cases} c_1, & \dot{\theta} > 0, \\ c_2, & \dot{\theta} < 0. \end{cases} \tag{5.3}$$

The function g varies according to the parameter in question. For example, if the parameter is c_1 then

$$g(t) = \begin{cases} -\dot{\theta}, & \dot{\theta} > 0, \\ 0, & \dot{\theta} < 0. \end{cases} \tag{5.4}$$

The initial conditions are $z(0) = 0$, $\dot{z}(0) = 0$ and there is a jump in the values of z and $\dot{z}$ at those points where $\dot{\theta} = 0$. Since $a_1(t)$ is positive for the experiment from which our data was obtained, we expect the homogeneous solution to (5.1) to be unstable, so the sensitivity of $\theta(t)$ with respect to a small perturbation in c_1 should increase with t.

Since $a_1(t)$ varies relatively slowly during certain time intervals, it should be relevant to consider the case for constant positive a_1. The system matrix for the left side of (5.1) is

$$A = \begin{bmatrix} 0 & 1 \\ a_1 & -a_2 \end{bmatrix},$$

whose eigenvalues are

(5.6) $$s = (-a_2 \pm [a_2^2 + 4a_1]^{1/2})/2.$$

As a_2 increases, the stable eigenvalue becomes more stable, and for sufficiently large a_2, the unstable eigenvalue approaches zero, though remaining positive.

High sensitivity with respect to initial velocity is also a problem because we attempt to fit the data on an interval starting about one second into the experiment and must approximate the initial angular velocity by a finite difference. For the sensitivity of $\theta(t)$ with respect to the initial value of $\dot{\theta}(t)$, the sensitivity equation is (5.1) with $g(t) = 0$ and $z(0) = 0$, $\dot{z}(0) = 1$. The same discussion of stability applies, but here it is interesting to note that the eigenvectors of A are $[1 \quad s]^T$. If a_2 becomes large, not only does the unstable s become small, but the component of $[z(0) \quad \dot{z}(0)]^T$ along the unstable eigenvector approaches zero.

Sensitivity analysis, then, suggests that we might reduce the difficulties caused by excessive sensitivity with respect to both unknown parameters and initial angular velocity by increasing the damping in the model. Fortunately, we can accomplish this by using the motor voltage instead of the motor torque as the input in (2.1).

Solving for $u(t)$ in equations (2.2) and (2.3) and substituting the result into (2.1) has the effect of adding a damping term due to back emf to the friction term. Using the damping model (2.5), the equation to be solved for θ becomes

$$\ddot{\theta} - \alpha \sin\theta + f(\tilde{c}_1, \tilde{c}_2, \dot{\theta}) = \tilde{\beta} v \tag{5.7}$$

where (5.7) may be compared with (2.4) by the equations

$$\tilde{\beta} = \beta K_t / R \tag{5.8}$$

$$\tilde{c}_i = c_i + \beta K_t K_e N/R, \quad i = 1,2. \tag{5.9}$$

Although much of this analysis rests on pretending that a time-varying coefficient in the sensitivity equation is constant, we believe that it is relevant because numerical results indicate that the solution to (5.7) is indeed much less sensitive to small variations in both model parameters and initial angular velocity. Figures 9 and 10 show the sensitivity of the solution to (5.7) with respect to small changes in β and $\tilde{c}_1$, respectively. The input v is the measured motor voltage in Figure 4. The values of $\tilde{c}_1$ and $\tilde{c}_2$ are much larger than in Figures 7 and 8 because they include the back emf term as shown in (5.8) and (5.9).

The reduced parameter sensitivity that results from including the back emf in the left side of (5.7) allows the search routine in our parameter identification algorithm to converge nicely from initial guesses corresponding to those in Table 1 (see Table 2). We find it interesting that including a physical term a certain way in the model eliminates a numerical difficulty from the parameter identification problem. The less sensitive model also yields much more reliable simulations.

6. FINAL PARAMETER IDENTIFICATION RESULTS

The iterative parameter estimation routine described in Section 3 was applied to model (2.4) on the time interval [1.0, 6.0]. The results for two similar initial guesses are given in Tables 1A and 1B. As shown in these tables, the parameter estimation routine is unstable and the cost function (3.2) may become quite large even for a good initial guess.

The results of the same routine for the desensitized model (5.7) with input given in Figure 4 are given in Tables 2A and 2B. The initial guesses were computed from the initial guesses for the corresponding Tables 1A and 1B by equations (5.8) and (5.9) using motor parameter values obtained in Section 3. The procedure shows convergence to low cost values on the time interval [1.0, 6.0].

Table 3 shows the results of an iterative procedure to obtain robust parameter estimates over the entire experiment. This table shows the values to which the estimation routine converged using successively longer time intervals. The converged values were used as the initial guess for the following interval. The optimal parameter values show little change between the intervals [1.0, 11.0] and [1.0, 17.0]. This indicates that a model developed with data on [1.0, 11.0] can predict the behavior of the system on [11.0, 17.0]. Figure 11 shows the fit-to-data of model (5.7) using the final parameter values in Table 3 over the interval [1.0, 17.0]. The graphs of model and data are almost indistinguishable in this figure.

The overall electro-mechanical model is reviewed in Table 4 along with our best estimates of its parameters. The electrical parameters (R, K_e, K_t) are those obtained in Section 3 from the data fit in Figure 6. The gear ratio (N) was supplied by ISRL. The physical parameters (I_0, mgr, damping coefficients) were obtained from the values of α, $\tilde{\beta}$, $\tilde{c}_1$, and $\tilde{c}_2$ given in Figure 11. It should be noted that since the manipulator was not disassembled for this experiment, these estimates are effective values for links 2 through 6 with an end-effector attached. These values will vary according to the type of end-effector and payload.

7. CONCLUSION

Our experience indicates the importance of actuator effects in the development of robust dynamic models for the motion of a robotic manipulator arm. Including natural damping due to back emf improved the performance of both the numerical integrator for solving the nonlinear equation of motion and the numerical optimizer for estimating parameters. Among the friction models we studied, the model allowing direction-dependent damping coefficients was the most successful.

We did not include higher order actuator effects such as drive shaft flexibility which have been found to be significant in some settings [6]. Our results indicate that for this experiment, higher order actuator dynamics did not improve the excellent fit-to-data results obtained with a simpler model. In continuing research we plan to test the model over a variety of complex motions of the robotic manipulator arm.

ACKNOWLEDGEMENT

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REFERENCES

[1] L. Keith Barker, "Kinematic equations for resolved-rate control of an industrial robot arm," NASA TM-85685, 1983.

[2] J. E. Bobrow, S. Dubowsky, and J. S. Gibson, "Time-Optimal control of robotic manipulators along specified paths," International Journal of Robotics Research, Vol. 4, Fall 1985, pp. 3-17.

[3] D. W. Brewer and J. S. Gibson, "Parameter identification for robotic manipulator arm," ICASE Report No. 85-42, NASA CR 178002, 1985.

[4] R. Fletcher, Practical Methods of Optimization, Vol. 1, John Wiley and Sons, 1981.

[5] C. William Gear, Numerical Initial Value Problems in Ordinary Differential Equations, Prentice-Hall, 1971.

[6] M. C. Good, L. M. Sweet, and K. L. Strobel, "Dynamic models for a control system design of integrated robot and drive systems," J. Dynamic Systems, Measurement, and Control, Vol. 107 (1985), pp. 53-59.

[7] B. K. Kim and K. G. Shin, "Suboptimal control of industrial manipulators with weighted minimum time-fuel criterion," IEEE Trans. Automatic Control 30 (1985), pp. 1-10.

[8] K. G. Shin and N. D. McKay, "Minimum-time control of robotic manipulators with geometric path constraints," IEEE Transactions on Automatic Control, Vol. AC-30, June 1985, pp. 531-541.

Table 1A. Torque Input Model
Time Interval: 1 sec - 6 sec

iteration	α	β	c_1	c_2	J
*0	13.00	16.00	4.000	4.000	399.0
1	13.15	16.10	4.400	4.074	159.0
2	12.95	16.03	3.910	3.980	94.4
3	12.96	16.04	3.908	3.985	.227

Table 1B. Torque Input Model
Time Interval: 1 sec - 6 sec

iteration	α	β	c_1	c_2	J
0	14.00	16.00	4.000	4.000	754.0
1	19.25	9.89	16.38	-7.630	174.0×10^4
2	16.76	13.02	12.72	-8.580	630.0
3	14.25	16.45	14.54	-1.940	310.0×10^7
4	16.54	13.32	12.89	-0.950	600.0

*The iteration number 0 indicates parameters supplied to the identification algorithm as starting values.

Table 2A. Voltage Input Model
Time Interval: 1 sec - 6 sec

iteration	α	$\tilde{\beta}$	$\tilde{c}_1$	$\tilde{c}_2$	J
0	13.00	1.470	41.71	41.71	0.5800
1	11.21	1.500	41.40	41.93	0.0230
2	11.71	1.700	47.46	48.37	0.0057

Table 2B. Voltage Input Model
Time Interval: 1 sec - 6 sec

iteration	α	$\tilde{\beta}$	$\tilde{c}_1$	$\tilde{c}_2$	J
0	14.00	1.470	41.71	41.71	1.4200
1	11.98	1.507	41.52	41.87	0.0410
2	11.67	1.700	47.27	48.16	0.0058

Table 3. Voltage Input Model Parameters Identified on Increasing Time Intervals

interval	α	$\tilde{\beta}$	$\tilde{c}_1$	$\tilde{c}_2$	J
1 sec - 6 sec	11.71	1.700	47.46	48.37	0.0057
1 sec - 11 sec	14.84	1.746	48.36	48.15	0.0290
1 sec - 13 sec	14.94	1.749	48.38	48.14	0.0360
1 sec - 17 sec	14.94	1.749	48.38	48.14	0.0470

Table 4.

Model equations:

$$I_0\ddot{\theta} - mgr\sin\theta + h(\mu_1, \mu_2, \dot{\theta}) = Nu$$

$$u = K_t i$$

$$Ri + K_e N\dot{\theta} = v$$

$$h(\mu_1, \mu_2, \dot{\theta}) = \begin{cases} \mu_1\dot{\theta}, & \dot{\theta} > 0 \\ \mu_2\dot{\theta}, & \dot{\theta} < 0 \end{cases}$$

Parameter estimates based on the model parameters in Figures 6 and 11:

Parameter	Parameter Definition	Estimate
I_o	effective moment of intertia	5.67 $kg\text{-}m^2$
mgr	gravitational torque	84.76 N-m
μ_1	viscous damping coefficient	19.65 N-m-sec
μ_2	viscous damping coefficient	18.29 N-m-sec
R	motor resistance	2.588 ohms
K_t	torque constant	0.238 N-m/amp
K_e	back emf constant	0.238 volts-sec
N	gear ratio	107.8*

*not estimated

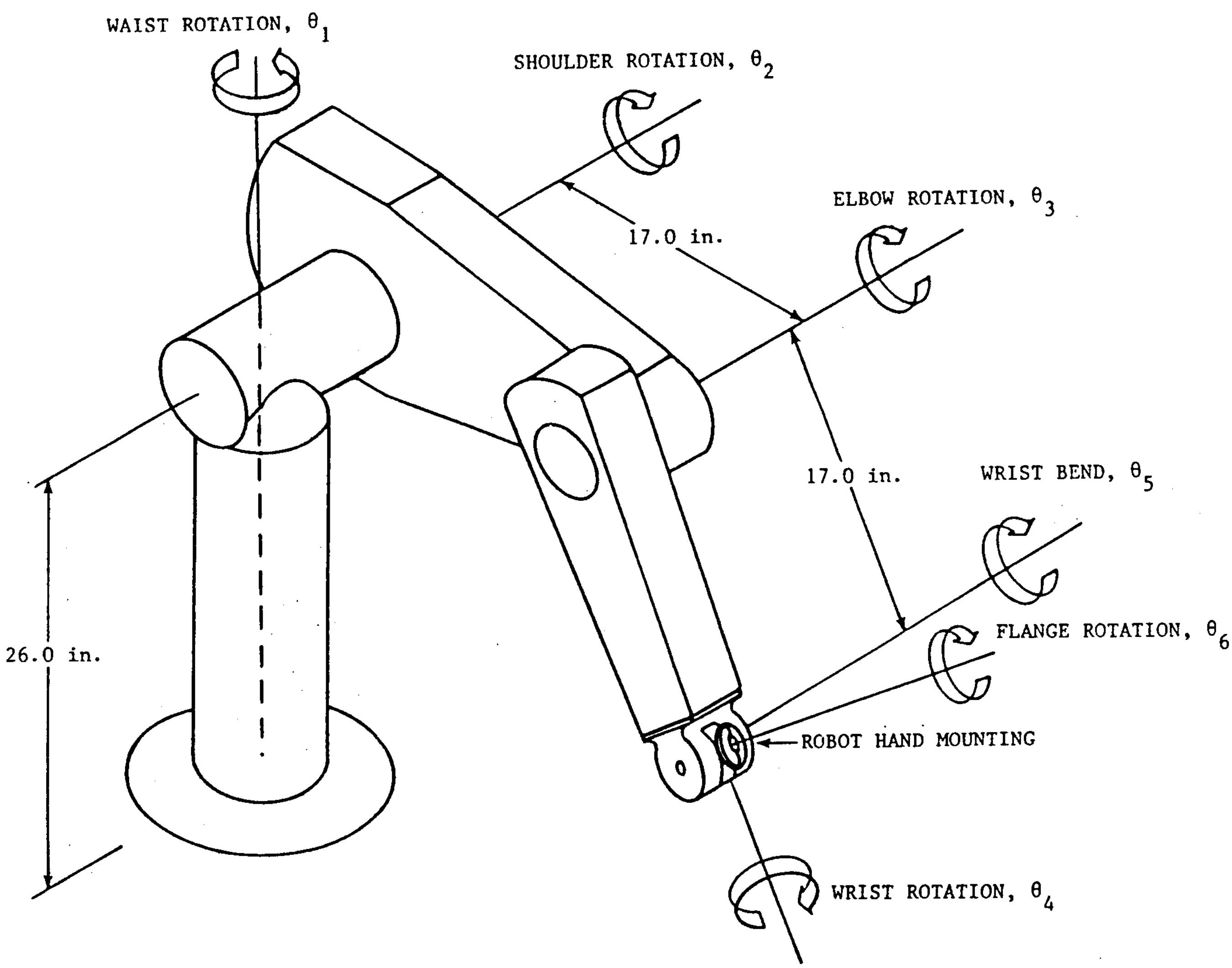


Figure 1. Robot arm with rotational joints [1].

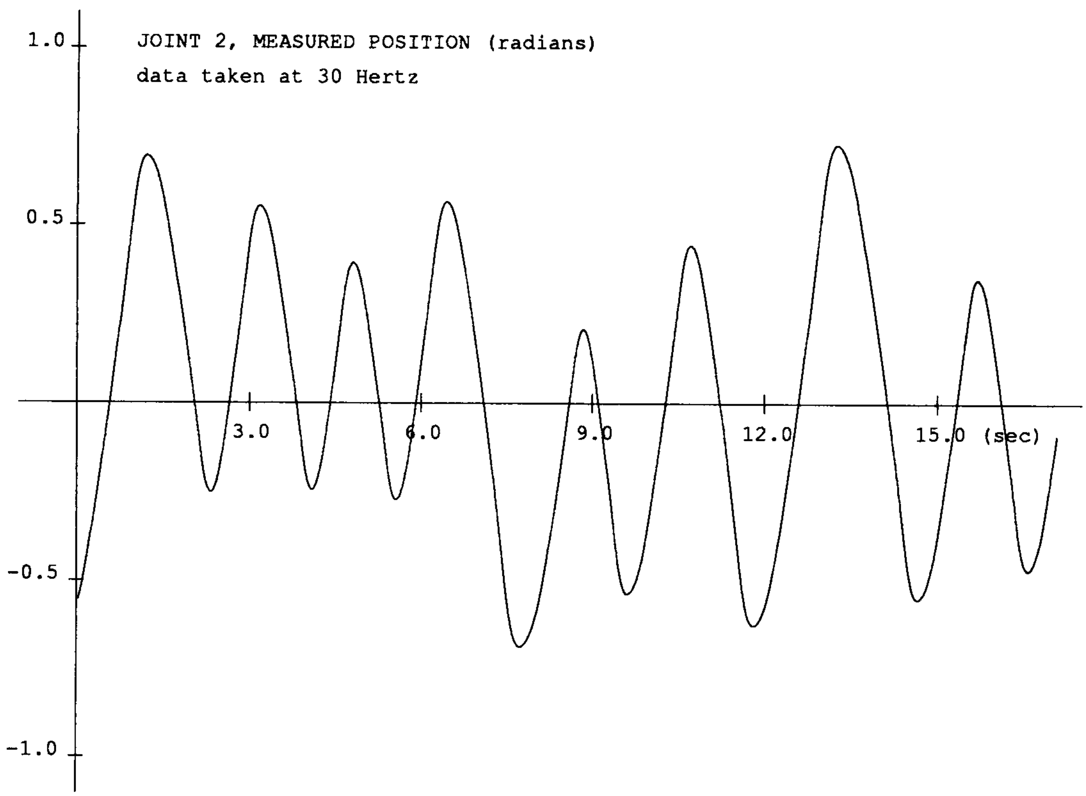
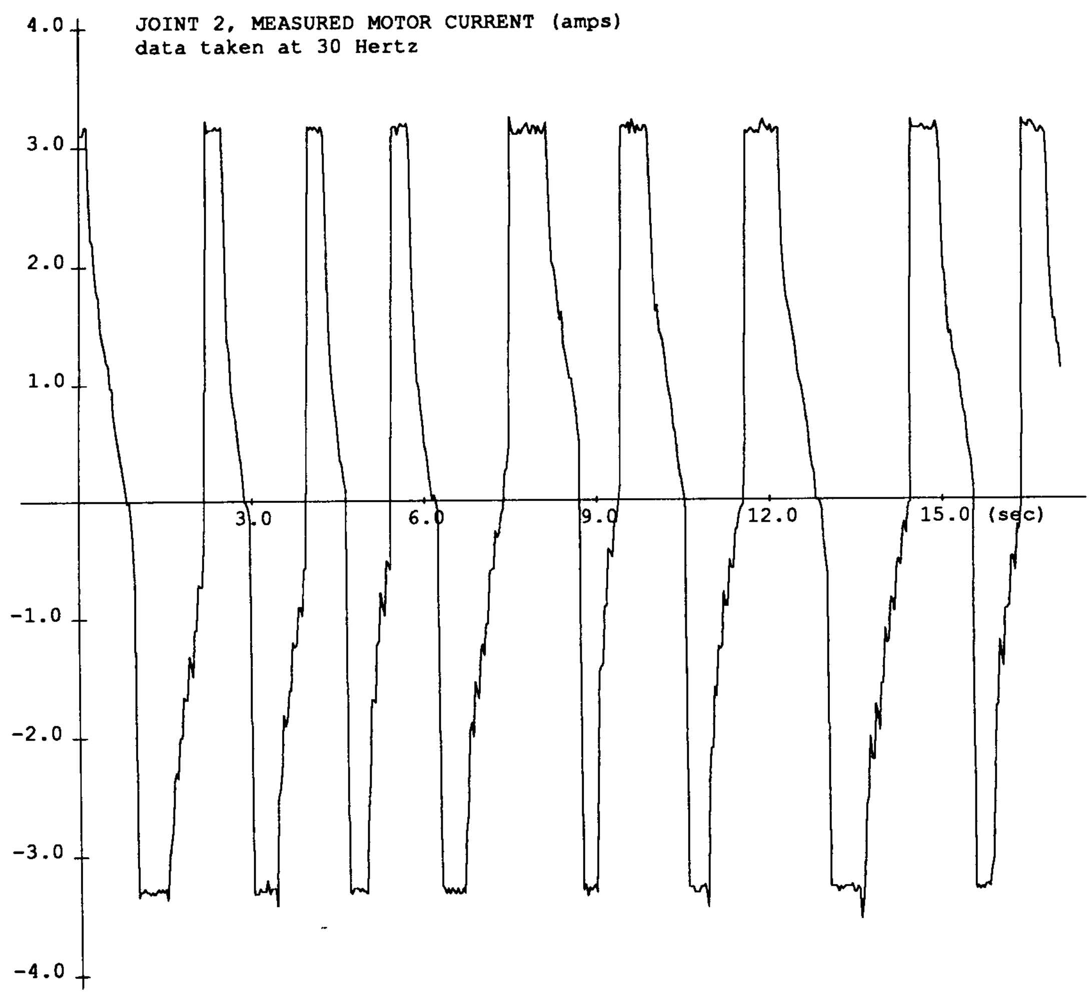

JOINT 2, MEASURED POSITION (radians)
data taken at 30 Hertz
1.0
0.5
-0.5
-1.0
3.0
6.0
9.0
12.0
15.0
(sec)

Figure 2



JOINT 2, MEASURED MOTOR CURRENT (amps)
data taken at 30 Hertz
4.0
3.0
2.0
1.0
-1.0
-2.0
-3.0
-4.0
3.0
6.0
9.0
12.0
15.0
(sec)

Figure 3

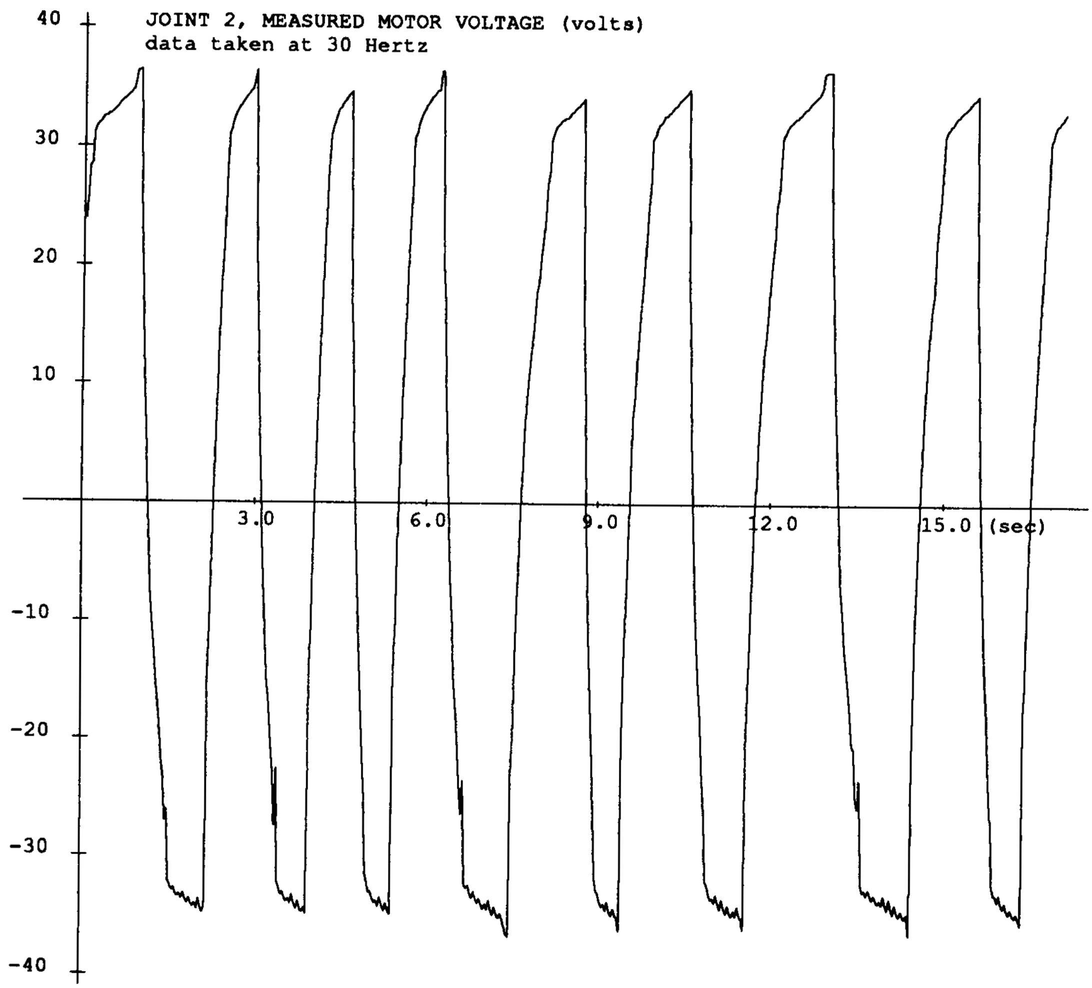

JOINT 2, MEASURED MOTOR VOLTAGE (volts)
data taken at 30 Hertz
40
30
20
10
-10
-20
-30
-40
3.0
6.0
9.0
12.0
15.0
(sec)

Figure 4

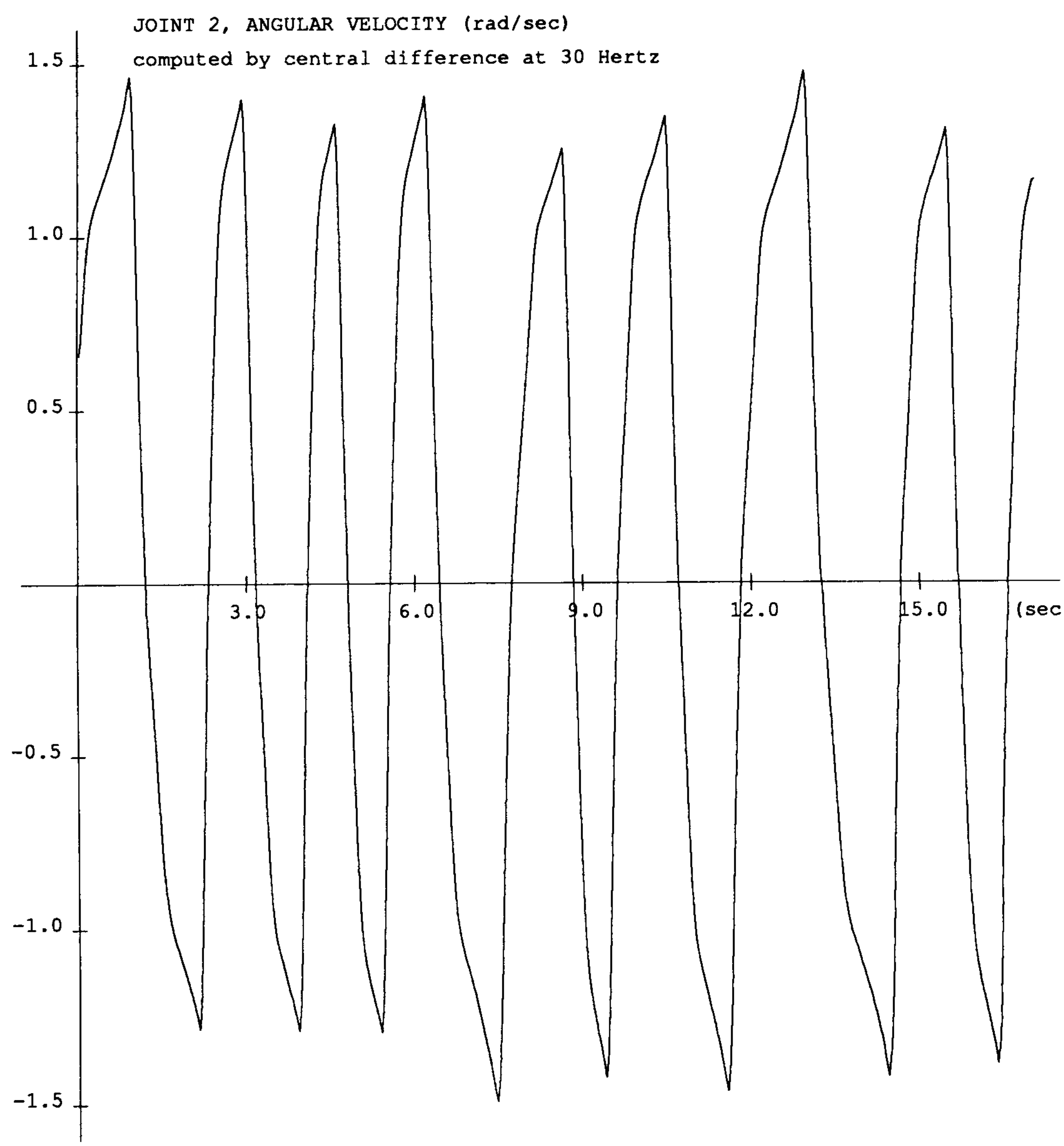

JOINT 2, ANGULAR VELOCITY (rad/sec)
computed by central difference at 30 Hertz
1.5
1.0
0.5
-0.5
-1.0
-1.5
3.0
6.0
9.0
12.0
15.0
(sec)

Figure 5

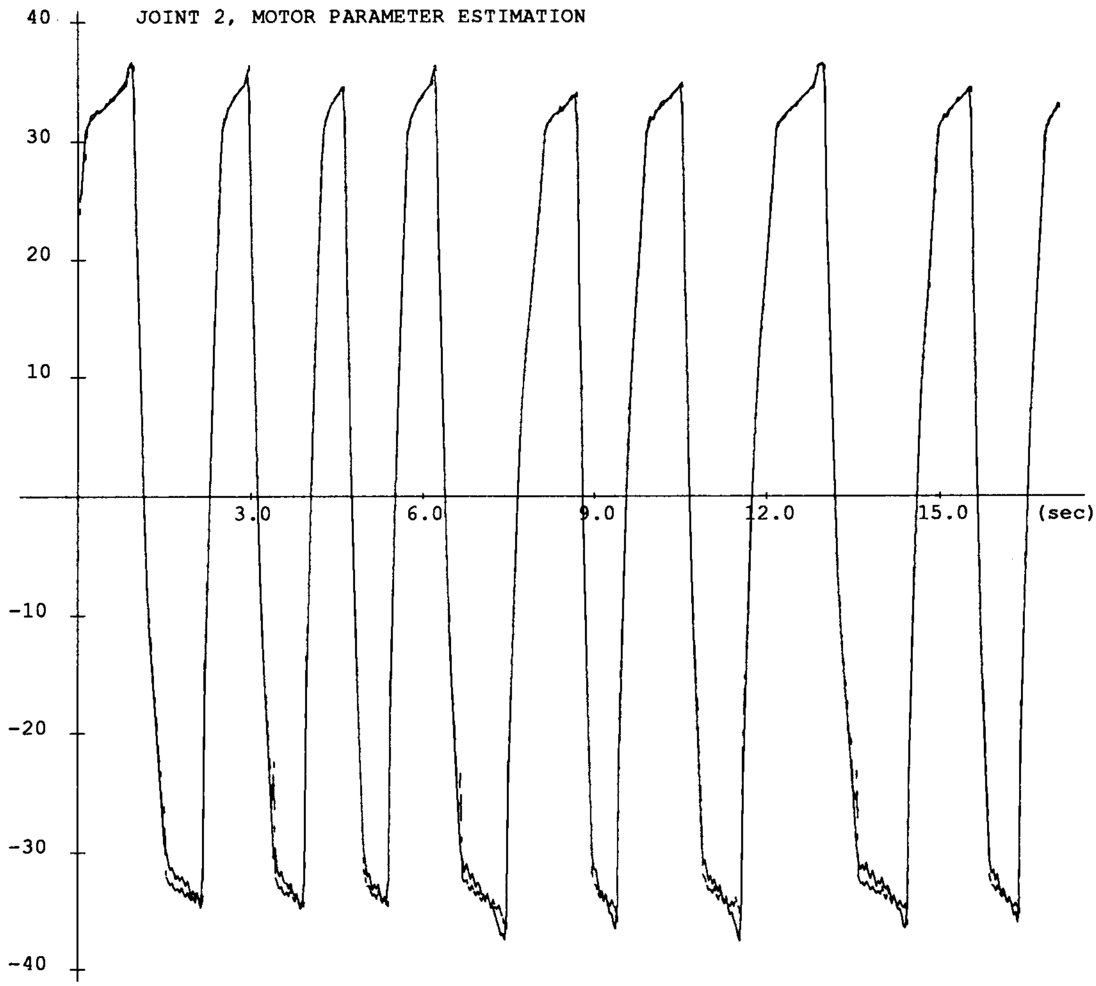


Figure 6. dashed curve -- measured motor voltage in volts

solid curve -- modeled motor voltage in volts

model = 2.588*current + 25.68*(angular velocity)

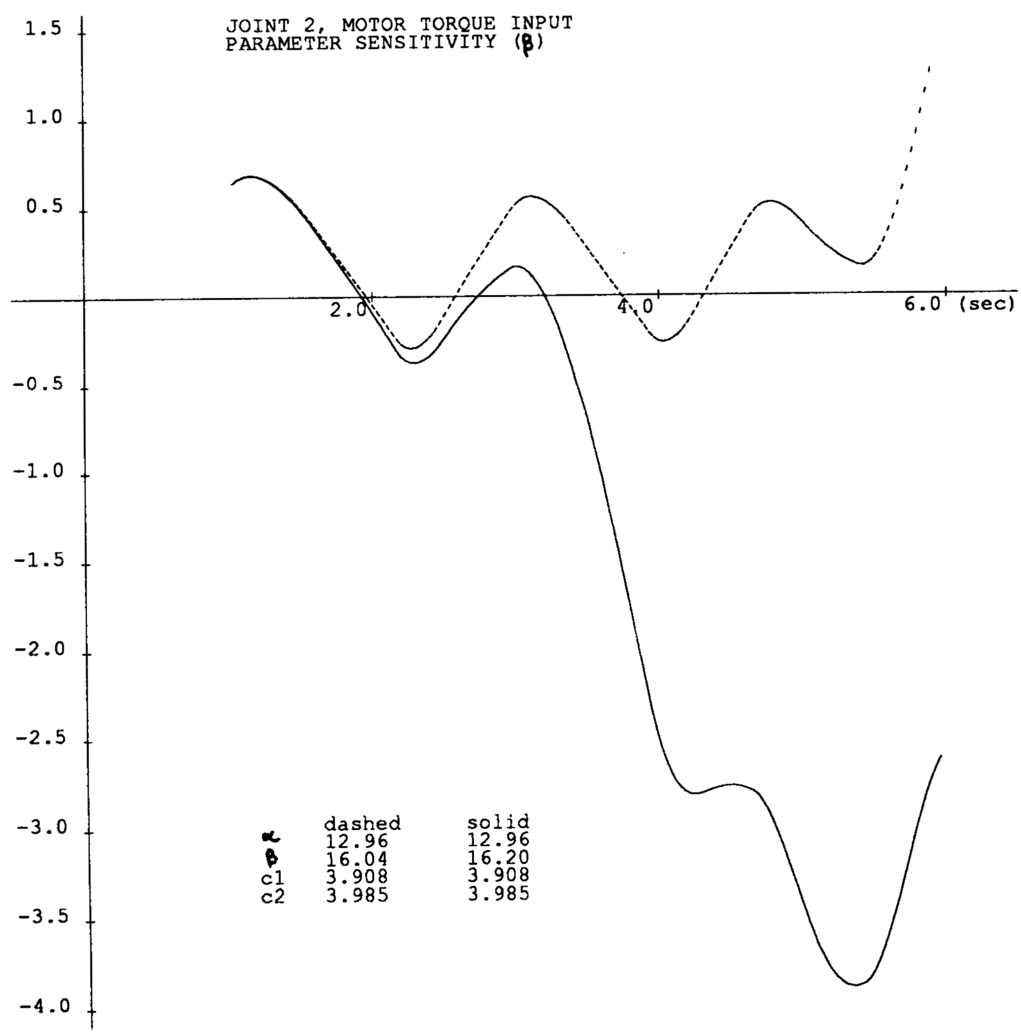

JOINT 2, MOTOR TORQUE INPUT
PARAMETER SENSITIVITY (β)
1.5
1.0
0.5
-0.5
-1.0
-1.5
-2.0
-2.5
-3.0
-3.5
-4.0
2.0
4.0
6.0 (sec)
dashed solid
α 12.96 12.96
β 16.04 16.20
c1 3.908 3.908
c2 3.985 3.985

Figure 7

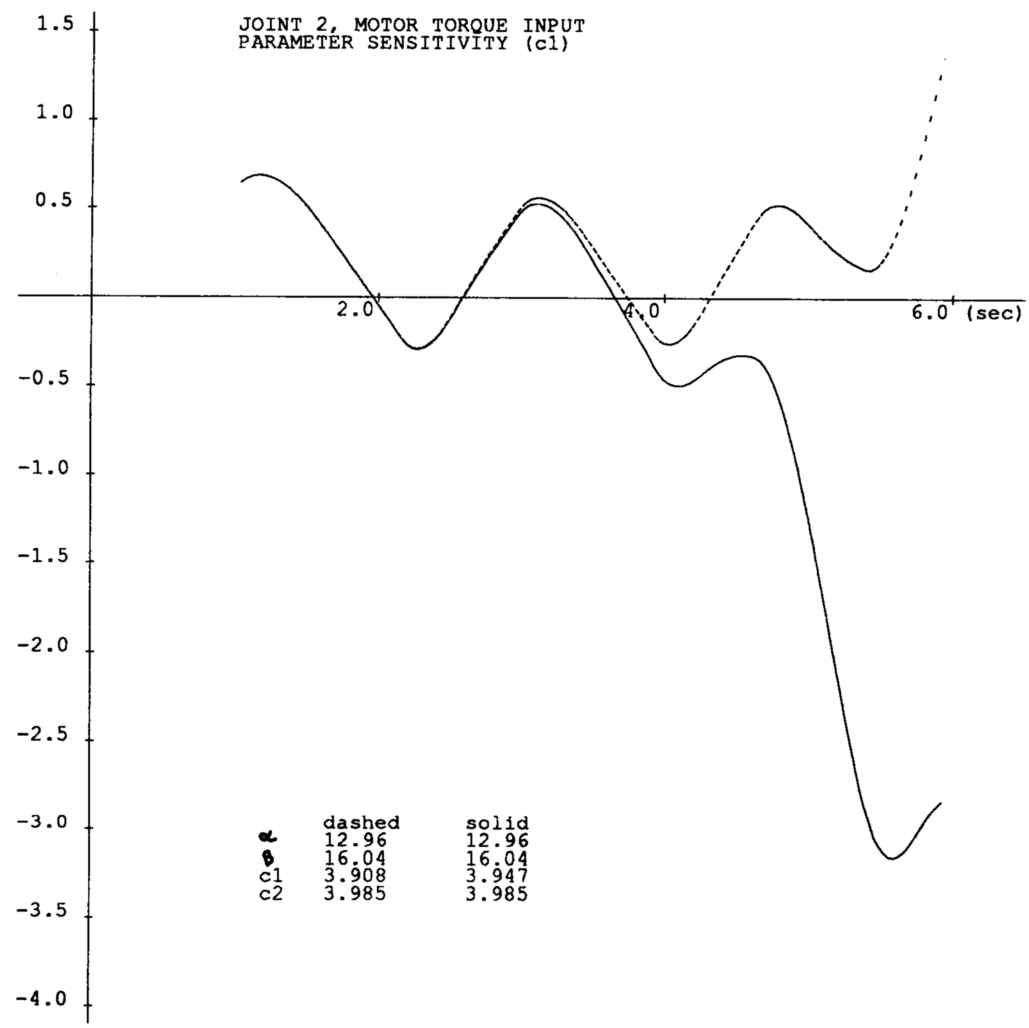

JOINT 2, MOTOR TORQUE INPUT
PARAMETER SENSITIVITY (c1)
1.5
1.0
0.5
-0.5
-1.0
-1.5
-2.0
-2.5
-3.0
-3.5
-4.0
2.0
4.0
6.0 (sec)
dashed solid
α 12.96 12.96
β 16.04 16.04
c1 3.908 3.947
c2 3.985 3.985

Figure 8

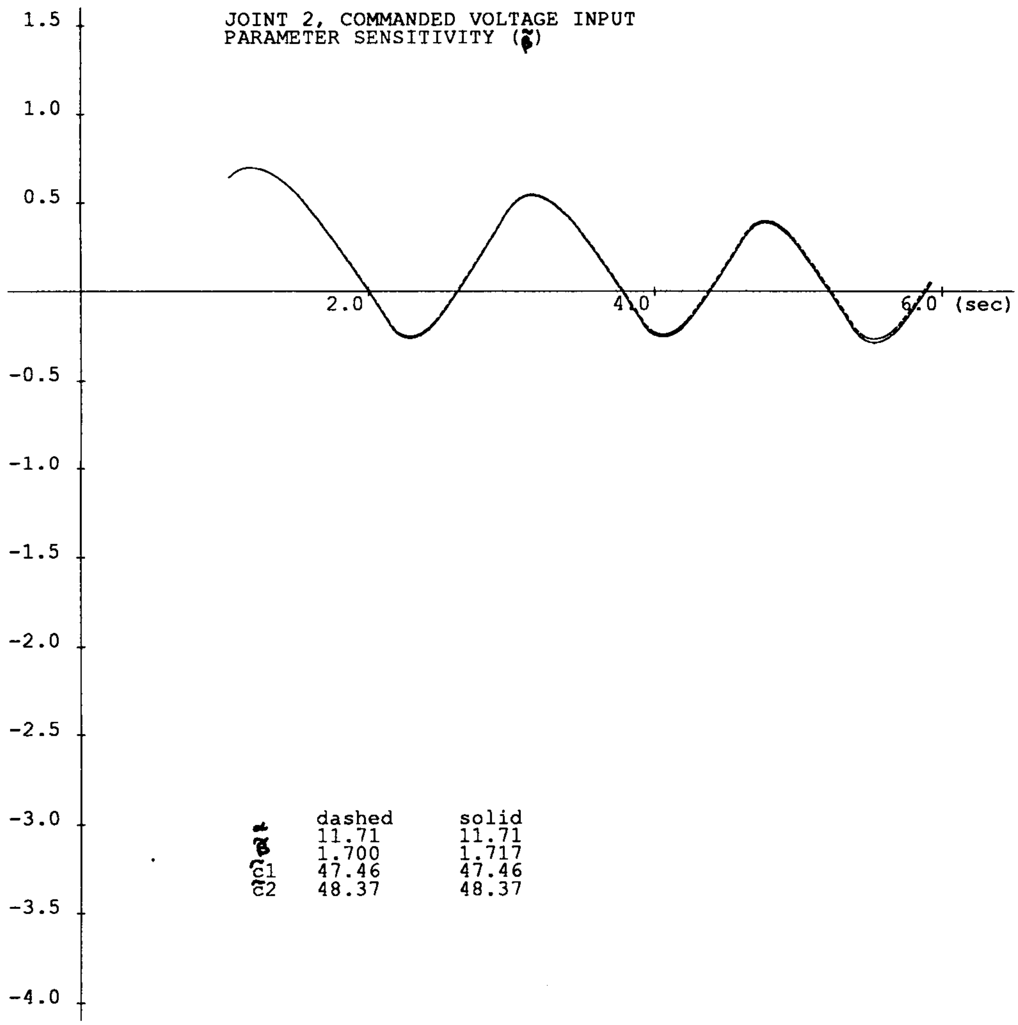

JOINT 2, COMMANDED VOLTAGE INPUT
PARAMETER SENSITIVITY (β̃)
1.5
1.0
0.5
-0.5
-1.0
-1.5
-2.0
-2.5
-3.0
-3.5
-4.0
2.0
4.0
6.0
(sec)
dashed solid
11.71 11.71
β̃ 1.700 1.717
c̃1 47.46 47.46
c̃2 48.37 48.37

Figure 9

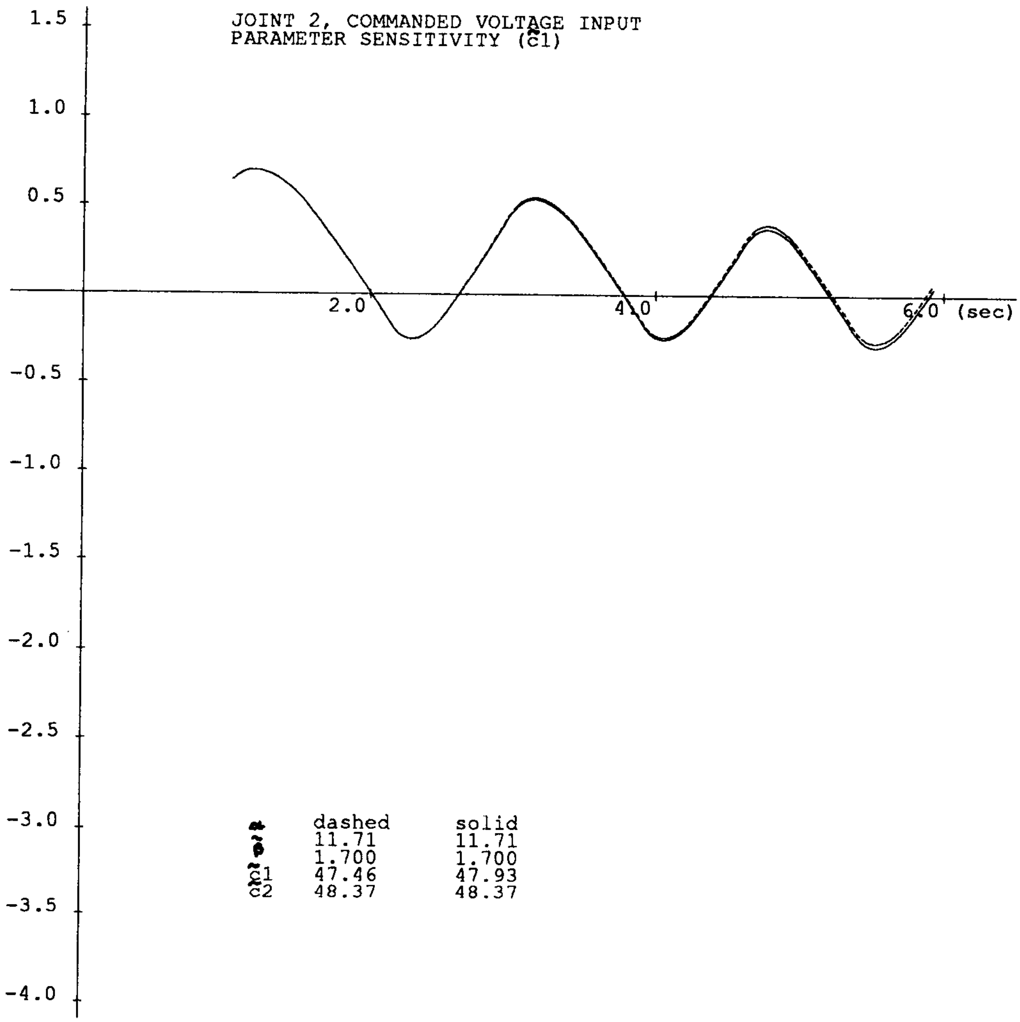

JOINT 2, COMMANDED VOLTAGE INPUT
PARAMETER SENSITIVITY (c̃1)
1.5
1.0
0.5
-0.5
-1.0
-1.5
-2.0
-2.5
-3.0
-3.5
-4.0
2.0
4.0
6.0
(sec)
dashed solid
11.71 11.71
1.700 1.700
c̃1 47.46 47.93
c̃2 48.37 48.37

Figure 10

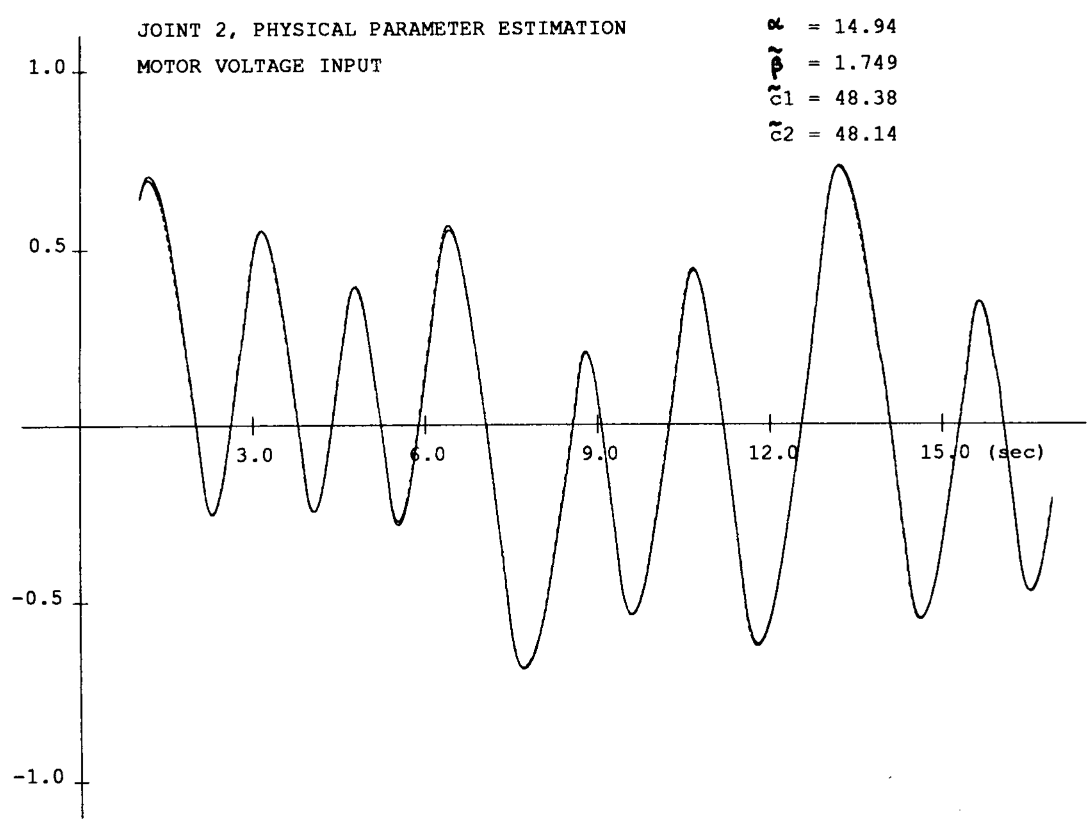


Figure 11. dashed curve -- measured position in radians

solid curve -- modeled position in radians

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16. Abstract

This paper describes the development of a nonlinear dynamic model for large oscillations of a robotic manipulator arm about a single joint. Optimization routines are formulated and implemented for the identification of electrical and physical parameters from dynamic data taken from an industrial robot arm. Special attention is given to difficulties caused by large sensitivity of the model with respect to unknown parameters. Performance of the parameter identification algorithm is improved by choosing a control input that allows actuator emf to be included in an electro-mechanical model of the manipulator system.

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